Building a student effort dataset: what can we learn from behavioral and physiological data

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Track

Academic research: comprehensive evaluations of recent innovations in learning and student analytics approaches.

1 Purpose

Decades of studies have shown that student's success is strongly dependent on their effort [1, 2, 3]. Recently, this concept made its way into the domain of Learning Analytics [4, 5]. One of the major difficulties of these works is to correctly define the effort and to find relevant means of measuring it. Our approach is based on the Cognitive Load Theory [6], which provides a theoretical background issued from Learning Sciences, desired by the Learning Analytics domain [7]. The cognitive load is a multidimensional construct that represents the load that performing a given task imposes on the cognitive system [8], and is often considered by researchers as being equivalent to mental effort [9]. The cognitive load has long been studied in educational sciences, and several types of measures have been proposed that can be classified into four categories [10]: (1) subjective measures, i.e., students' perceived effort, (2) performance measures, e.g., the outcome of student work assessments, (3) physiological measures, such as pupil dilation and heart rate, and (4) behavioral measures, such as points of fixations, and keyboard and mouse usage.

In an exploratory work [11], we proposed a new cognitive load measurement model based on behavioral data. Our data consisted in keyboard and mouse usage, as well as page views and fixation points from an eye tracker, and were collected in the context of an online Esperanto course. Our results showed that eye tracking data provided a better indication of effort than keyboard, mouse and page view data, and that a slight complementarity exists between these two types of information. In the same spirit, Larmuseau et al. [12] investigated the correlation between the cognitive load and two physiological measures from smart watches: skin conductance and skin temperature. The participants were future school teachers taking a course as part of their training. One of their main findings is a moderate correlation between effort and skin conductance. However, both these last approaches are preliminary and only focused on small samples (less than 20 participants).

2 Design

In order to propose a more meaningful and reliable model of cognitive load measurement, we undertook the collection of a much richer dataset involving 120 students from lower secondary education (from the 5^{th} cycle in French schools, which is equivalent to the 7^{th} grade in the United States). In this experiment, students wore a smartwatch to capture their hand movements and heart rate. We also collected gaze data using eye-trackers as well as mouse and keyboard usage data. We could therefore collect data related to all four types of aforementioned measures of the cognitive load.

The participants had to complete a sequence of 15 English exercises, each of which was followed by a questionnaire evaluating how much effort they exerted. At the beginning and at the end of the session, they also answered an additional questionnaire related to their overall fatigue and stress. The sessions lasted between 30 and 60 minutes and the students completed the exercises at their own pace, i.e., each student solved a different number of exercises. Some students skipped a few exercises because they had not studied the content related to it.

3 Results

The results of a preliminary analysis will be presented during the conference. Our analysis seeks to know if we can reproduce or enhance the results of the model presented in [11] by correlating behavioral measures with subjective measures (instead of scores). For this, we apply to our new dataset a similar methodology to that of the aforementioned paper [11]. We believe that our approach can be exploited to develop different effort-based tools to help both teachers and students. We are especially planning to incorporate the resulting measurements to a teacher dashboard with the goal to help teachers identify students who are not engaged into learning or students exerting too much effort, as well as teaching material tailored to the engagement of the students. The proposed model could also be used in fully automated tools. Especially, recommendation systems could be proposed that aim at maximizing students' engagement based on how much effort they exerted and they can exert.

5 Acknowledgments

This work is funded by the PIA E-FRAN METAL project.

6 References

[1] L. Hill, "Effort and reward in college: A replication of some puzzling findings," *Journal of Social Behavior & Personality,* pp. 151-161, 1990.

[2] O. H. Swinton, "The effect of effort grading on learning," *Economics of Education Review,* vol. 29, no. 6, p. 1176–1182, 2010.

[3] A. P. Scariot, F. G. Andrade, J. M. C. da Silva and H. Imran, "Students Effort vs. Outcome: Analysis Through Moodle Logs," in *IEEE 16th International Conference on Advanced Learning Technologies*, Austin, TX, USA, 2016.

[4] R. Nagy, "Tracking and Visualizing Student Effort: Evolution of a Practical Analytics Tool for Staff and Student Engagement," *Journal of Learning Analytics*, pp. 165-193, 2016.

[5] J. Samuelsen and M. Khalil, "Study effort and student success: a MOOC case study," in *21th International Conference on Interactive Collaborative Learning*, 2018.

[6] J. Sweller, "Cognitive load during problem solving: Effects on learning," *Cognitive Science*, vol. 12, no. 2, p. 257–285, 1988.

[7] D. Suthers and K. Verbert, "Learning analytics as a "middle space"," in *Proceedings of the Third International Conference on Learning Analytics and Knowledge (LAK'13)*, Leuven, Belgium, 2013.

[8] F. Paas and J. J. Van Merriënboer, "Instructional control of cognitive load in the training of complex cognitive tasks," *Educational Psychology Review*, vol. 6, no. 4, p. 351–371, 1994.

[9] J. Leppink, "Cognitive load theory: Practical implications and an important challenge," *Journal of Taibah University Medical Sciences*, vol. 12, no. 5, p. 385–391, 2017.

[10] F. Chen, J. Zhou, Y. Wang, K. Yu, S. Z. Arshad, A. Khawaji and D. Conway, Robust multimodal cognitive load measurement, Springer, 2016.

[11] B. Moissa, G. Bonnin, S. Castagnos and A. Boyer, "Modelling students' effort using behavioral data," in *Workshop de la conférence Learning Analytics and Knowledge*, 2019.

[12] C. Larmuseau, P. Desmet, L. Lancieri and F. Depaepe, "Investigating the Effectiveness of Online Learning Environments for Complex Learning," in *Learning Analytics and Knowledge*, 2019.